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The RUT Factor: Analysing Changes in Student Readiness to Undertake Tasks with Generative AI as a Moderator

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(Ibrahim & Iqbal, 2025)

Abstract: This study investigates the moderating role of Generative Artificial Intelligence (GAI) on student academic readiness, operationalised by the RUT Factor Model (Readiness to Undertake Tasks) - a triadic construct comprising of emotional, cognitive and behavioural readiness. A quasi-experimental interventional design was utilised with 100 undergraduate psychology students, who were divided via Randomised Controlled Trials (RCT) into a control group and an AI-assisted test group. Both groups had to complete an academic task, with the AI-assisted group given access to a structured prompt guide for ChatGPT, while the control group resorted to traditional study methods. Paired samples t-tests showed significant improvements in cognitive and behavioural readiness in the test group, echoed by similarities in the independent samples t-test. Multiple regression analyses showed the AI-intervention to be a significant predictor of cognitive and behavioural readiness, but not emotional readiness. The findings suggest that structured use of GAI enhances task-preparedness without inducing emotional regulation. Future research owing to related limitations are also discussed.

Keywords: AI, Artificial Intelligence, Generative Artificial Intelligence, ChatGPT, cognitive readiness, behavioural engagement, pedagogy, RUT Factor model, self-regulated learning, intervention study.

INTRODUCTION:

In recent years, Artificial Intelligence (AI) has emerged as a transformative tool in multiple sectors, specifically so in education. The rise of Generative AI (GAI), with the public access of ChatGPT in 2022, redefined how students interacted with course content, research, instructors and one another (Kasneci et al., 2023). GAI also encompassed personalised learning platforms, and AI-driven assessment evaluation technologies like TurnItIn, a tool utilised by educational institutions to track submission credibility and plagiarism (Sahana & Poornachandra, 2023). The rapid integration of GAI into the educational paradigm aided in adaptive instruction and streamlined feedback loops (Shribala & Jhaneswaran, 2024; Bajpai, 2024). As AI is increasingly embedded within educational landscapes, its influence on students' readiness to undertake academic tasks – especially surrounding cognitive, behavioural and emotional readiness – warrants a critical examination.

Whilst AI is attached to benefits such as personalisation and task execution efficiency (Dilmi & Sakri, 2024; Bit et al., 2024), it has also introduced concerns surrounding overdependence, inequity and academic integrity (Sytniakivska & Kulish, 2024; Yadav & Sharma, 2024), with more universities opting to return to written examinations as the preferred mode of assessment, owing to rising uncertainty in AI-detection software (Scarfe et al., 2024). This literature review provides a structured synthesis of existing research on the relationship between AI and student readiness, coalescing into the development of a novel framework – the RUT Factor (Readiness to Undertake Tasks) – and setting the premise for empirical investigation.

Beyond its role in instructional logistics automation, AI's integration into pedagogical ecosystems has catalysed how cognitive, emotional and behavioural readiness is both measured and maintained. Intelligent Tutoring Systems (ITS) remains a mainstay of AI-enhanced instruction, with research positing significant support for individualised learning paths and reduced cognitive load (Lin et al., 2023) – specifically in STEM education (Sadiku et al., 2021). Sarfaraj (2025) found that ITSs leveraging conversational AI models, can improve student engagement and dynamic scaffolding. Yet, ITS implementation tends to succumb to scalability and personalisation limitations, eradicating generalisability. Similarly, adaptive e-learning mechanisms integrating ChatGPT among other Large Language Models (LLMs) found improved satisfaction and outcomes as per Alshammari (2025), albeit with a narrow scope of participants, raising concerns on external validity. However, their effectiveness in developing higher order critical analysis skills remains unverified, with conflicting evidence regarding short-term improvements in comprehension, but a lack of sustainability in long-term conceptual retention (Zhou & Hou, 2024).

Behaviourally, AI tools like ChatGPT foster time-on-task and motivational gains, but findings are limited by context. Kanwal (2025) found improvements in thought organisation and writing resilience among L2 English learners, while Kim et al. (2025) found that emotional attachment to ChatGPT was predictive of sustained use. Conversely, prolonged affective dependence may risk "technodependence" (Benita et al., 2025), where an emotional reliance on AI may displace human support structures.

Cognitively, AI effectiveness is still nuanced. Elshansky (2021) identified cognitive fatigue and a decline in deep processing among individuals resorting to over-automation of AI-systems. Dubey et al. (2024) further posited that whilst AI may enhance superficial fluency, it may erode metacognitive problem-solving capabilities over time.

Understanding student readiness to undertake academic tasks – specifically in AI-integrated environments – requires a framework that would encompass the cognitive, emotional and behavioural nuances of learning. This study integrates four theoretical underpinnings – the Self-Regulated Learning Theory (SRLT), the Social-Emotional Learning Models (SELM), the Technology Acceptance Model (TAM) and the Technology Readiness Index 2.0 (TRI).

Philosophically, the study adopts an ontologically critical realist perspective, with readiness viewed as a stratified, emergent construct, comprising of observable behaviours shaped by unobservable mechanisms and contextual variables. This standing assumes that AI and learner agency co-constructs readiness to undertake tasks – neither deterministically technological nor purely volitionary.

Epistemologically, the study is pragmatic, leveraging positivist (psychometrics and performance) and constructivist (attitudes) approaches to evaluate the multidimensional nuances of task-readiness. This pluralistic lens enables a methodological triangulation without privileging one form of knowledge creation over another.

SRLT (Zimmerman, 2002) is central to this study. It posits that learners actively manage their cognitive resources, emotional stages and strategic behaviours through repetitive cycles of planning, monitoring and reflection. SRLT has been adapted to technology-mediated contexts (Panadero, 2017), including "socially shared regulation" during AI collaboration (Jarvela & Hadwin, 2024).

SELM complement SRLT by focusing on intrapersonal and interpersonal dynamics. SEL competencies of self-awareness, self-management and social awareness are increasingly mediated by AI tool-use (Zong & Yang, 2025), offering feedback loops that further influence academic emotions and resilience.

TAM explains cognitive-behavioural responses to digital tools through perceived usefulness and ease of use (Davis, 1989). However, TAM's limited explanatory power, owing to its minimal emotional granularity, poses a potential limitation to the study.

To address this, the TRI is incorporated into the study. The four sub-scales – optimism, innovativeness, discomfort and insecurity – capture student affective orientations toward AI (Parasuraman & Colby, 2015). A high TRI score has been positively associated with increased engagement with AI and behavioural readiness (Zong & Yang, 2025), while high discomfort or insecurity has been linked to technology-induced anxiety and withdrawal.

The combination of the aforementioned frameworks scaffolds the RUT Factor model, providing a theoretically robust and epistemologically pluralist foundation for understanding AI-mediated academic readiness.

Student readiness is a multi-dimensional construct that reflects the degree to which students are prepared to initiate, sustain, regulate and execute academic engagement. Within the proposed Readiness to Undertake Tasks (RUT) model, the study delineates readiness into three interdependent domains – cognitive, emotional and behavioural. Although often treated as discrete variables, empirical evidence underscores the dynamic interplay of the three, specifically in technology-integrated pedagogical landscapes (Kundu & Bej, 2024; Manwaring, 2017).

Cognitive readiness refers to a student's capacity for metacognitive regulation, working memory engagement and attentional control (Crameri et al., 2021). While AI-integrated platforms, particularly those which include adaptive feedback mechanisms, have shown potential to scaffold these functions (Guo, 2020), the extent of this benefit is not uniformly supported. For example, Jyoti et al. (2023) found that while AI tools did improve decision-making and attention regulation for a short term, they risked reduced student initiative for independent problem solving – particularly when active engagement was replaced by automation. Furthered by Elshansky's (2021) findings, long-term use of AI tools led to declining cognitive flexibility. Furthermore, Koshova et al. (2021) argue that cognitive readiness must include meta-awareness of learning strategies, something current AI systems rarely assess or enhance.

Emotional readiness includes the student's capacity for self-regulation, affective stability and resilience pertaining to academic stressors (Lakshmi & Lyngdoh, 2024). Studies show that emotional engagement is a key predictor of performance in AI-supported tasks (Huang, 2024). However, the effect of AI on emotional readiness is still ambivalent. Guo (2020) identified dopamine-mediated affective responses to AI systems that can ambivalently bolster and also derail learning via hyperstimulation or over-attachment. Benita et al. (2025) warned that emotional bonding with AI agents can supplant human support systems, producing technodependence. Similarly, Kundu & Bej (2024) found that AI use was correlated with both decreased frustration and an increased perception of social isolation – specifically when feedback loops lacked an interpersonal specificity.

Behavioural readiness reflects the student's effort investment, persistence and proactive task management (Kennedy & Hampshire, 2025). This domain is most visibly enhanced by AI through increased time-on-task and reduced procrastination (Shevchenko, 2021). However, this behaviour is often misinterpreted as genuine agency. Bandaranaike and Wilson (2015) cautioned that behavioural indicators of readiness may mask underlying emotional disengagement, especially when systems reward surface compliance rather than reflective action. Moreover, performance gains in AI-assisted contexts may be artificially inflated due to automated scaffolding that can serve to obscure student actual learning and competence (Fantuzzo et al., 2017).

Thus, the literature reveals a troubling pattern, wherein AI can both amplify readiness metrics and obfuscate true student capacity. The overreliance on behavioural proxies (login frequency or task completion time) without methodological triangulation of emotional and cognitive indicators can misdiagnose readiness levels. Therefore, a valid assessment of student RUT in AI-enhanced environments must distinguish academic readiness from apparent engagement.

The integration of GAI into educational ecosystems has reshaped student academic engagement across cognitive, behavioural and emotional dimensions. Unlike earlier AI iterations limited to rule-based instruction, GAI's dialogic and natural language capabilities enable more personalised, autonomous and context-sensitive interactions. However, the empirical evidence surrounding its actual effect on student readiness is mixed and deeply nuanced.

Cognitively, GAI offers real-time ideation, clarification and synthesis that may reduce extraneous cognitive load (Park & Kim, 2025). In programming tasks, students using ChatGPT (GAI) significantly outperformed those using traditionally static resource banks like StackOverflow, suggesting an enhanced procedural fluency due to GAI. However, Fan et al. (2024) argued that these improvements may come at the expense of "metacognitive laziness" – where learners outsource reflective processing to the GAI model, thereby diminishing deep learning and transferability of skills. Similarly, Acosta-Enriquez et al. (2024)

found that while students reported increased ease of task completion, cognitive readiness does not linearly correlate with durable conceptual understanding.

Emotionally, ChatGPT's immediacy and responsiveness can buffer academic stress and foster satisfaction (Kim et al., 2025). However, these same affective benefits can lead to dependency and reduced resilience. Wong & Viberg (2024) found that students using GAI for peer feedback in writing tasks exhibited reduced anxiety but also lower ambiguity tolerance. The emotional regulation hence facilitated by GAI appears contingent on the nature and context of interaction – whether it is exploratory, passive or confirmatory.

Behaviourally, GAI tools have been associated with increased motivation, persistence and readiness to undertake challenging tasks. Ahmed et al. (2024) found that 68% of participants in a multi-university survey attributed better task initiation and completion rates to access to GAI. However, performance gains may be more nuanced. Wecks et al. (2024) found that GAI users scored an average of 6.71 points lower on unaided assessments than a control group, suggesting an inflated and flawed self-perception of readiness. Pellas (2024) further found that while creativity mediated improved performance, GAI did not significantly aid critical thinking or long-term retention.

Critically, very few studies satisfactorily differentiate between task support and cognitive scaffolding, often conflating the two in GAI contexts. Tang et al. (2024) emphasise that while GAI boosts performance expectancy and learning, it risks reinforcing surface-level engagement unless paired with structured metacognitive prompts.

In sum, GAI acts as a moderator of perceived readiness, enhancing short-term outcomes but potentially masking or eroding long-term academic capabilities. For readiness to be authentically developed, GAI must be embedded within pedagogical frameworks to emphasise reflection, epistemic humility and autonomy. The RUT Factor Model provides a lens to disentangle these layers, mapping the interplay between tool, learner and context.

Despite the prolific studies focused on AI in education, significant conceptual, empirical and methodological gaps remain in understanding how AI – and more specifically GAI – moderates student readiness across cognitive, emotional and behavioural domains.

A key limitation in the current literature is the overrepresentation of short-term, superficial outcomes, such as task efficiency, ease of use, or grade improvements (Acosta-Enriquez et al., 2024; Park & Kim, 2025). Very few studies disaggregate these from genuine learning readiness or consider long-term implications surrounding metacognitive resilience or knowledge transfer. Fan et al. (2024) posited that GAI fostered "metacognitive laziness", yet the field lacks a systematic framework to map where enhanced performance ends and disengagement begins.

Furthermore, there is a bias in discipline and demographic in the current research. Most empirical literature is concentrated in programming (Fernu et al., 2024), business (Mission & Fio, 2024) or language learning (Chang & Sun, 2024), excluding fields like psychology, humanities or social science. Additionally, findings are found to be generalised beyond their empirical score (Tierney et al., 2024). This study addresses the need for context specific investigation within psychology undergraduates, where emotional and cognitive readiness are especially salient.

The emotional dimension of readiness remains under-explored. While some studies measure anxiety or life-satisfaction (Kim et al., 2025; Wong & Viberg, 2024), very few engage with emotional ambivalence, dependence and withdrawal from GAI overuse (Benita et al., 2025). Likewise, AI-driven feedback systems are rarely evaluated for emotional authenticity or empathy, leaving a critical gap in assessing interpersonal displacement (Xiao et al., 2025).

From a methodological standpoint, most studies rely on performance proxies or retrospective survey data. There are very few interventional studies that track multidimensional temporal changes (Marchena Seklie et al., 2024). Moreover, few studies employ validated multidimensional instruments that span cognitive, emotional and behavioural axes (Chang & Sun, 2024), thus complicating triangulating true readiness beyond engagement metrics.

This novel study responds to these gaps by introducing and empirically testing the RUT Factor Model, wherein it:

1. Defines readiness as a triadic construct encompassing cognitive, behavioural and emotional readiness.
2. Uses a structured GAI intervention to investigate how AI moderates these components over time.
3. Incorporates an interventional design with validated measures.

By situating this study within the critical realist ontology and pragmatic epistemology, it addresses the lack of philosophical reflexivity in AI-readiness research. The aim is not merely to evaluate AI's impact but to examine how readiness is co-constructed by learner agency, affective regulation and AI mediation. Thus, the hypotheses for this study are as follows:

H1: Students in the AI-assisted group will show significantly greater improvements in cognitive readiness post-intervention than those in the control group.

H2: Students in the AI-assisted group will show significantly greater improvements in behavioural readiness post-intervention than those in the control group.

H3: Students in the AI-assisted group will not show significantly greater improvements in emotional readiness post-intervention than those in the control group.

METHODOLOGY

Study Design

This study employed a quasi-experimental, interventional, between-groups design. The primary aim was to examine the impact of a structured GAI intervention on undergraduate psychology students, specifically pertaining to academic readiness, operationalised as a triadic construct – cognitive, behavioural and emotional readiness – defined as the RUT Factor Model.

Participants were randomly allocated into two groups – an AI-assisted intervention group (n=50) and a non-AI control group (n=50). Both groups completed an identical academic task at baseline and post-intervention. The AI group was provided structured access to ChatGPT with a specific set of modifiable prompts, while the control group completed the task using only traditional self-regulation strategies.

The study utilised standardised psychometric instruments for each readiness subscale before and after the intervention. This design aided in evaluating intra- and inter-group differences.

Materials

1. Generative AI Tool

The intervention employed ChatGPT, accessed via the official OpenAI interface. A structured prompt guide was provided to participants to ensure standardised usage. This included guidance on feedback, clarification, and general outlines – without directly outsourcing entire answers. The AI tool was embedded within the academic task to support cognitive structuring and behavioural initiation, while limiting over-reliance. The non-AI group received identical task instructions but no AI access or guidance.

2. Baseline Measures

A 33-item integrated quantitative measure, constructed from existing validated measures was used:

- Cognitive Readiness

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Metacognitive Awareness Inventory (Schraw & Dennison, 1994) – 8 items.

- Emotional Readiness

    Academic Self-Efficacy Scale (Chemers et al., 2001) – 5 items.
    State-Trait Anxiety Inventory (Marteau & Bekker, 1992) – 5 items.

- Behavioural Readiness

    Self-Regulated Learning Strategies Questionnaire (Pintrich et al., 1991) – 6 items.
    Procrastination Assessment Scale for Students (Solomon & Rothblum, 1984) – 3 items.

- AI Orientation

    Technology Readiness Index 2.0 (Parasuraman & Colby, 2015) – 3 items.
    Technology Acceptance Model (Davis, 1989) – 3 items.

3. Academic Task

Participants completed a 250-word critical response essay on a psychology topic relevant to their curriculum. Task performance was evaluated using a rubric covering structure, clarity and criticality.

Participants

A total of 100 undergraduate psychology students (Mean age = 20.4 years, SD = 1.7; 72% female, 28% male) were recruited from universities in the UAE and India to participate in the study. Recruitment was conducted via WhatsApp and Email circulations. All participants were enrolled in a developmental psychology module at the time of study, ensuring familiarity with academic content.

Via an RCT, participants were split into two (n=50) for the control and intervention groups.

Inclusion criteria required the following:

1. Participants be current second- or third-year undergraduate psychology students.
2. Participants have undergone a developmental psychology module either currently or in the past year.

Procedure

The study was conducted within a 45-minute session. Upon joining the Zoom call, participants were assigned anonymised ID codes and provided with a brief overview of the study's purpose. Upon providing informed consent, they were randomly allocated into two groups (n=50 each) using a random number generator.

The session began with a 10 minute slot for the pre-test measure, where participants completed the quantitative measure via Microsoft Forms. Subsequently, participants were asked to begin their task – a 250-word critical response essay ("Briefly discuss how attachment theory explains social development in early childhood with one example to support your answer.") – by splitting off into separate breakout rooms based on their group allocation. The intervention group used the provided prompt guide, whilst the control group executed the task independently. After the 20-minute intervention, participants retook the 33-item quantitative measure. Following this, they were debriefed and thanked for their participation.

Ethical Considerations

The study was conducted in accordance with the BPS Code of Ethics, with additional safeguards implemented for digital, AI-integrated, and online research contexts.

1. Informed Consent and the Right to Withdraw

All participants received a detailed information sheet outlining the study's aim, participant rights and data confidentiality protocols. Informed consent was obtained via a Microsoft Form before the

Zoom session began. Participants were further informed of their right to withdraw from the study at any time before the completion of the study without penalty.

2. Privacy and Monitoring

Participants were asked to keep their cameras on throughout the 45-minute study to ensure academic integrity. However, no video recordings were made. The use of cameras was clearly justified in the consent materials and information sheet.

3. Data Handling and Anonymity

Participant data was anonymised on all submitted measures. Identifiable data like email addresses and demographics were stored separately and deleted immediately after data analysis.

In addition to the enforcements above, participants were made aware of accessible mental health resources in the possibility of any distress.

Analysis and Data Preparation

All quantitative data was exported into IBM SPSS Statistics (v29) for data analysis. Data was screened for missing values, outliers and normality violations. Boxplots and Z-scores aided in identifying and removing univariate outliers exceeding SD = ±3.29.

All questionnaire measures were verified for internal consistency via Cronbach's alpha, will all domains exceeding the acceptable threshold ($\alpha > .7$). Primary analyses of data included a paired-samples t-test for within-group change evaluation, an independent-samples t-test for inter-group change evaluation. AI orientation (TAM and TRI) was retained for exploratory analysis but not included in the primary model. A series of multiple linear regressions were carried out for each post-test readiness domain as a dependent variable, including pre-test readiness scores as the covariate and the group allocation as well.

Assumptions of normality, multicollinearity (VIF < 5), homoscedasticity and linearity were tested and met.

RESULTS

Descriptive Statistics and Reliability

Descriptive statistics for all variables are summarised in Table 1. Internal consistency for all composite readiness subscales met required limits, with Cronbach's $\alpha > .7$. No significant skewness or kurtosis was observed in any variable (absolute values < 1), supporting the appropriateness of parametric testing.

Domain	AI Group Pre-test Mean (SD)	AI Group Post-test Mean (SD)	Control Group Pre-test Mean (SD)	Control Group Post-test Mean (SD)	Cronbach's Alpha
Cognitive Readiness	4.08 (0.64)	4.61 (0.58)	4.09 (0.61)	4.18 (0.65)	0.84
Emotional Readiness	3.92 (0.70)	4.05 (0.68)	3.90 (0.73)	3.95 (0.75)	0.78

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Behavioural Readiness	4.11 (0.68)	4.58 (0.60)	4.08 (0.71)	4.16 (0.69)	0.81

Table 1: Descriptive statistics and scale reliability scores.

Paired Samples t-tests

Within the AI-assisted group, significant improvements were observed in both cognitive readiness, t(49) = 5.91, p < .05, d = .84, and behavioural readiness, t(49) = 4.71, p < .01, d = .66. Emotional readiness showed a non-significant increase, t(49) = 1.53, p = .13. No significant changes were found between pre- and post-test scores in any of the readiness domains in the control group.

Independent Samples t-tests

Independent samples t-tests were conducted to compare post-test readiness scores between the test and control groups. As hypothesised, there were statistically significant differences in both cognitive readiness, t(98) = 3.48, p < .05, d = .70, and behavioural readiness, t(98) = 3.29, p < .05, d = .56, with the test group (AI-assisted) outperforming the control group in both domains.

However, the between-group differences in emotional readiness were surprisingly not statistically significant, t(98) = .70, p = .48, d = .14. While both groups showed moderate within-group changes in emotional readiness, this lack of a between-group difference is unexpected.

Multiple Linear Regression Analysis

To assess the unique effect of group allocation on post-test readiness, whilst controlling for baseline differences, three multiple regressions were conducted.

Model 1: Cognitive Readiness

- F(2,97) = 21.48, p < .05; Adjusted R^2 = .29
- Pre-test cognitive readiness: ß = .47, p < .05
- Group allocation: ß = .35, p < .05

Model 2: Emotional Readiness

- F(2,97) = 1.92, p = .15; Adjusted R^2 = .02
- Pre-test emotional readiness: ß = .28, p = .041
- Group allocation: ß = .12, p = .22

Model 3: Behavioural Readiness

- F(2,97) = 18.07, p < .001; Adjusted R^2 = .26
- Pre-test behavioural readiness: ß = .45, p < .05
- Group allocation: ß = .33, p < .001

Summary of Findings

Table 2 provides a summarised overview of the quantitative data analysis that was conducted in this study.

Domain	t (within AI)	p	d	t (between groups)	p	d	Regression Adjusted R^2	Group β	Group p
Cognitive Readiness	5.91 (df = 49)	< .05	0.84	3.48 (df = 98)	< .05	0.70	0.29	0.12	< .05
Emotional Readiness	1.53 (df = 49)	.13	–	0.70 (df = 98)	.48	0.14	0.02	0.12	.22
Behavioural Readiness	4.71 (df = 49)	< .01	0.66	3.29 (df = 98)	< .05	0.56	0.26	0.33	< .001

Table 2: Summarised overview of quantitative findings.

DISCUSSION

This study aimed to investigate how structured GAI interventions influence student readiness to undertake academic tasks, operationalised through the RUT Factor – a triadic model encompassing cognitive, behavioural and emotional readiness. Grounded in Self-Regulated Learning Theory (Zimmerman, 2002), Social-Emotional Learning Models (Zins et al., 2004), the Technology Acceptance Model (Davis, 1989) and the Technology Readiness Index 2.0 (Parasuraman & Colby, 2015), the study hypothesised that GAI-supported students would demonstrate superior improvements in readiness domains compared to their non-AI counterparts.

The findings partially supported these hypotheses, with paired samples t-tests within the AI-assisted group revealing statistically significant improvements in cognitive readiness and behavioural readiness, but not in emotional readiness. Independent samples t-tests confirmed significant between-group differences in post-test cognitive and behavioural readiness, with the AI group outperforming controls, whereas emotional readiness differences were not statistically significant. These findings were reinforced by multiple regression analyses showing group allocation as a significant predictor of post-test cognitive and behavioural readiness, but not emotional readiness.

Collectively, the results suggest that structured GAI use enhances student cognitive and behavioural preparedness for academic tasks, aligning with emerging literature on AI-enhanced learning practices (Kasneci et al., 2023; Noy & Zhang, 2023; Zawacki-Richter et al., 2019), but with minimal impacts on emotional development (Kim et al., 2025; Wong & Viberg, 2024). This nuanced pattern calls for a deeper investigation into the psychological mechanisms that underpin AI's impact on academic readiness, especially as emotional resilience emerges as a critical dimension in digital pedagogical landscapes (Pekrun et al., 2002; D'Mello & Graesser, 2012).

The most pronounced outcome of this study was the significant improvement in cognitive readiness observed in the AI-assisted group relative to the control group. This supports prior findings that GAI tools like ChatGPT can act as a cognitive scaffold, enhancing ideation, reducing extraneous cognitive load and supporting structured academic reasoning (Li et al., 2024). The within-group effect size aligns with prior studies demonstrating that learners using ChatGPT outperform peers in critical reasoning tasks, particularly when scaffolded by instructional prompts (Abdulla et al., 2024). These findings are further corroborated by evidence that postgraduate students perceive ChatGPT as an "intellectual collaborator," facilitating metacognitive regulation and higher-order planning (Aldulaijan & Almalky, 2025).

However, while the observed gains confirm short-term cognitive facilitation, the long-term implications are yet to be discerned. Fan et al. (2024) raised concerns about "metacognitive laziness", whereby learners overly depend on AI tools for synthesis and explanation, potentially weakening the development of independent problem-solving capacity. Dubey et al. (2024) similarly found that although GAI enhances comprehension fluency, it can erode deep learning when students are not prompted to reflect on AI-generated content. This study partially supports this – although the AI-supported group outperformed the control group in post-test scores, the reliance on structured prompts raises the question of whether students were internalising the processes or merely following AI suggestions.

The moderate ß coefficient in the regression model indicates that even when controlling for baseline performance, group allocation contributed meaningfully to post-intervention cognitive readiness. This confirms the predictive utility of AI access in enhancing metacognitive outcomes, particularly in structured tasks. This is supported by Lee & Park (2023), who found that students with higher self-regulated learning capacities reported more strategic use of ChatGPT, further suggesting that cognitive gains from AI are moderated by pre-existing SRL traits.

Nevertheless, the risk of over-automation cannot be overlooked. Studies by Valcea et al. (2024) argue that ChatGPT's strength in clarifying lower-order concepts may inadvertently suppress effortful engagement with more complex content unless AI interaction is coupled with reflective scaffolds. Similarly, Chakurova (2024) warned that while GAI enhances expressive fluency and reading comprehension, it can disincentivise cognitive persistence in less motivated students.

Thus, these findings validate the RUT model's cognitive domain while cautioning against uncritical reliance on GAI tools. The findings highlight the need for instructional design strategies that incorporate AI not merely as a response generator but as a metacognitive partner – prompting elaboration, self-questioning and cognitive monitoring. Therefore, while AI has the potential to amplify cognitive readiness, its efficacy is maximised only when embedded within frameworks that promote strategic and reflective engagement.

In line with the third hypothesis, the present study anticipated that emotional readiness would not show significant improvement following the GAI intervention. This was empirically supported by both the independent samples t-test and the regression model, which indicated no statistically significant difference between the two groups in post-intervention emotional readiness scores. While the within-group change showed a minor upward trend in the test group, the absence of a between-group significance warrants a deeper interpretation.

This outcome reflects broader trends in existing literature, where emotional engagement and regulation do not appear to be automatically enhanced by AI use. Generative AI tools like ChatGPT are often designed to optimise efficiency, information access and fluency – not necessarily to foster affective growth or resilience (Chan & Tsi, 2024). Several empirical studies have noted that while GAI platforms can reduce superficial anxiety during task execution, they do not consistently elicit the emotional regulation processes necessary for long-term affective development (Sung et al., 2025; Chakurova, 2024).

Theoretical models like the SELM emphasise the need for social reciprocity, empathy and interpersonal reinforcement in cultivating emotional competence – factors currently underdelivered in AI-mediated academic contexts (Keshishi & Hack, 2023). AI may offer responsive feedback, but without emotional context or authenticity, its affective impact is limited. Emotional readiness – inclusive of resilience, affective regulation and academic self-efficacy – typically develops through reflective and interpersonal processes that GAI cannot emulate (Pekrun et al., 2002; Yin et al., 2024).

Furthermore, existing research points to the significant moderation role of student perception and engagement with GAI tools on the emotional outcomes of AI use. Students with high levels of perceived control and technological optimism – a measure evaluated by the TRI – are more likely to benefit from AI use affectively (Wang & Yin, 2025). Conversely, passive or dependent engagement with GAI often results in lower ambiguity tolerance and diminished emotional resilience (Zabojnik & Hromada, 2024).

There is also a rising concern regarding emotional displacement – wherein student begin to rely on GAI tools for psychological reassurance – leading to technodependence (Benita et al., 2025). Whilst such tools may temporarily alleviate stress, they fail to build the emotional competencies necessary for autonomous learning, as found by Kim et al. (2025), wherein albeit students reported reduced stressed, they also exhibited a greater difficulty in peer collaboration and emotion-centric reflection.

Ultimately, this study's null finding in emotional readiness does not indicate that GAI has no affective impact, but rather that its emotional influence may be too superficial or situational to result in measurable gains in trait-like readiness constructs. Future research would benefit from exploring longer-term AI engagement and integrating affect-sensitive AI design principles to better support emotional regulation and academic resilience.

Finally, this study found that students in the AI-assisted group demonstrated significantly greater improvements in behavioural readiness than their counterparts in the control group, both through paired t-test analysis and independent samples t-testing. These outcomes were further supported by the multiple regression model, where group allocation emerged as a strong predictor of post-test behavioural readiness, even after controlling for pre-test scores. These findings affirm the second hypothesis and offer compelling support for the moderating role of GAI in enhancing behavioural engagement.

Behavioural readiness improvements suggest that GAI may reduce initiation latency, providing immediate scaffolding and reinforcing self-monitoring practices. Prior research by Xu et al. (2023) found that learners who used AI feedback systems showed shorter task initiation times and increased persistence, corroborating the present study's direction of effect. Similarly, Tsai et al. (2022) reported that students using structured prompts with ChatGPT displayed greater task completion consistency over a 3-week period than students using unstructured AI tools.

Crucially, AI's role in scaffolding aligns with Vygotsky's (1978) concept of the Zone of Proximal Development, wherein support structures or scaffolds help learners bridge gaps in independent task execution. GAI may serve as such a scaffold by virtue of real-time guidance, thereby narrowing the behavioural readiness gap. However, unlike human scaffolding, AI lacks social reciprocity and adaptive empathy – key contributors to sustained behavioural change (Winne & Hadwin, 2008). While the GAI tool used in this study increased compliance and task persistence, the extent to which this reflects genuine strategic learning versus surface-level task adherence remains undiscerned.

Behavioural gains could also be influenced by perceived accountability due to the structured format of AI engagement. Mou & Xu (2024) suggest that when students are prompted to explain their input to AI systems, they exhibit greater task ownership. Moreover, the structured prompt guide provided in this study likely played a critical role. Research has highlighted the impact of guided AI use on better performance and lower procrastination rates than free-form or unguided AI interaction (Lu et al., 2023).

Nevertheless, scholars caution against interpreting such improvements as unequivocally positive. Behavioural readiness may be inflated by AI-induced over-scaffolding, where students complete tasks due to algorithmic efficiency over personal volition (Leary et al., 2024). In a longitudinal study, Weinstein et al. (2023) found that students using AI for academic planning developed fewer independent goal-setting strategies over time, highlighting the tension between short-term performance and long-term autonomy yet again.

Additionally, the potential for behavioural displacement has emerged as a concern. van Alten et al. (2023) argue that AI-assisted task execution may reinforce reactive study habits over proactive ones if not coupled with metacognitive support. In this study, the lack of qualitative data limits the ability to parse behavioural motivations, which future research may address via longitudinal designs or thematic analysis.

The demographic composition of the sample may also bear relevance, as prior meta-analyses suggest that gendered patterns in help-seeking and self-discipline may moderate behavioural responses to AI (Pajares, 2002; Bong & Skaalvik, 2003). As such, the effects observed in this study may not be universally replicable across broader academic populations.

Thus, the study offers strong empirical evidence for the role of GAI in improving behavioural readiness. Yet, findings should be contextualised within the limitations of scaffolding fidelity and the complex interplay between behavioural indicators and authentic learner autonomy. Structured AI interventions appear effective in reducing behavioural friction in task execution, but their impact on deeper behavioural self-regulation remains to be fully explored.

The broader educational and theoretical implications of this study are worth noting. The improvements in cognitive and behavioural readiness underscore the educational potential of structured GAI interventions, aligning with the increasing body of evidence suggesting that AI tools embedded in pedagogically coherent frameworks, can act as accelerators of learning efficiency and engagement (Krstic et al., 2022; Zawacki-Richter et al., 2019).

However, the modest impact on emotional readiness reveals a cautionary perspective. Therefore, educational stakeholders must resist simplistic AI-as-solution narratives and alternatively develop blended curricula that couple AI tools with human mentoring, metacognitive scaffolds and interpersonal dialogue (Selwyn et al., 2021).

One critical tension is the balance between over-usage and enhancement, with scholars like Luckin et al. (2016) and Holmes et al. (2022) arguing that if AI provides too much support, students become passive consumers, antithetical to self-regulated learning principles. This dilemma echoes Ryan & Deci's (2023) Self-Determination Theory, wherein autonomy, competence and relatedness are posited as psychological needs that drive intrinsic motivation. If AI support circumvents effortful learning, students may meet competence needs without autonomy, leading to transient amotivation (Deci & Ryan, 2012). Thus, designers of AI-based learning environments must balance cognitive scaffolding with strategic difficulty, creating necessary difficulties that foster learning resilience (Bjork & Bjork, 2011).

The structured deployment of GAI in this study – using controlled Zoom environments, standardised prompt guides and scaffolded academic tasks – stands in contrast to real-world academic settings, where students often engage with AI tools autonomously, informally and without oversight, raising critical questions regarding access, training and academic integrity.

Educational institutions must develop policies that integrate AI literacy into curricular competencies, differentiate between permissible and impermissible use cases and train faculty to detect and manage AI-supported assignments (Smutny & Schreiberova, 2020; UNESCO, 2023). Moreover, digital divide issues persist – students with less access to AI tools or training may fall behind peers, reinforcing existing educational inequalities (Selwyn & Jandric, 2020).

While the present study advances the understanding of AI's moderating role in student readiness, several limitations must be acknowledged. The limited sample size and predominantly female demographic limits generalisability of findings across disciplines, genders, educational levels and cultural contexts. The short-term design of this study, while revealing improved cognitive and behavioural readiness, fails to provide clarity on the longitudinal consistency of these effects. Furthermore, the nature of intervention may have limited emotional dynamics and interpersonal regulation. Although a structured prompt guide was used, individual differences in interpretation and interaction may have introduced variability. Individual differences in AI literacy or comfort were not explicitly controlled for either. Finally, while all utilised quantitative measures were validated, they remain subjective, introducing potential for inherent bias.

Future research should adopt repeated measures over multiple semesters or academic years to track the temporal stability of the aforementioned effects. Cognitive scaffolding may initially support performance but foster dependency over time. Educational institutions must invest in AI literacy interventions to control for individual differences in prompt engineering capabilities to cultivate reflective use, reduced technodependence and stronger cognitive autonomy. Introducing multimodal metrics, such as psychometric, behavioural and physiological measures may increase granularity in understanding readiness, reducing reliance on single-source subjective self-report data. Furthermore, future investigation should evaluate how personalised emotional and cognitive feedback from AI tools impacts self-regulated learning cycles. Finally, the absence of statistically significant group differences in emotional readiness invites deeper exploration, possibly with a qualitative parallel measure as well.

Thus, this study provides empirical evidence for the moderating role of GAI in enhancing undergraduate psychology students' readiness to undertake academic tasks, by operationalising readiness through the novel RUT Factor Model. GAI serves best as a cognitive augmentor, enhancing metacognitive fluency and behavioural initiation without fundamentally altering emotional regulation capacities. In conclusion, this study contributes to a growing field that not just examines what AI can do for education, but what education must do for itself as well.

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